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| journal or publication title | IET Communications |
| volume | 9 |
| number | 3 |
| page range | 375-385 |
| year | 2015 |
| URL | http://hdl.handle.net/10258/00009476 |

doi: info:doi:10.1049/iet-com.2014.0337

# A Game-Theoretic Approach to Energy-Efficient Resource Allocation in Device-to-Device Underlay Communications

Zhenyu Zhou, Mianxiong Dong, Kaoru Ota, Ruifeng Shi, Zhiheng Liu, and Takuro Sato

*Abstract*—**Despite the numerous benefits brought by Device-to-Device (D2D) communications, the introduction of D2D into cellular networks poses many new challenges in the resource allocation design due to the co-channel interference caused by spectrum reuse and limited battery life of User Equipments (UEs). Most of the previous studies mainly focus on how to maximize the Spectral Efficiency (SE) and ignore the energy consumption of UEs. In this paper, we propose a distributed interference-aware energy-efficient resource allocation algorithm to maximize each UE's Energy Efficiency (EE) subject to its specific Quality of Service (QoS) and maximum transmission power constraints. We model the resource allocation problem as a noncooperative game, in which each player is self-interested and wants to maximize its own EE. A distributed interference-aware energy-efficient resource allocation algorithm is proposed by exploiting the properties of the nonlinear fractional programming. We prove that the optimal solution obtained by the proposed algorithm is the Nash equilibrium of the noncooperative game. We also analyze the tradeoff between EE and SE and derive closed-form expressions for EE and SE gaps.**

***Keywords*—*Energy-efficient, device-to-device, resource allocation, interference-aware, tradeoff***

## I. Introduction

Device-to-Device (D2D) communications underlaying cellular networks bring numerous benefits including the proximity gain, the reuse gain, and the hop gain [1]. The D2D communication session setup and management issues in the Long Term Evolution (LTE) System Architecture Evolution (SAE) were addressed in [2], and simulation results have demonstrated that the total throughput of the overall cellular network can be increased significantly.

However, the introduction of D2D communications into cellular networks poses many new challenges in the resource allocation design due to the co-channel interference caused by spectrum reuse and limited battery life of User Equipments (UEs). A large number of works have been done on how to perform resource allocation in an interference-limited environment. A Stackelberg game based resource allocation scheme was proposed in [3], in which the Base Station (BS) and the D2D UEs were modeled as the game leader and followers respectively. Another Stackelberg game based scheme was proposed in [4], in which the cellular UE rather than the BS was modeled as the game leader. A two-stage resource allocation scheme which employs both the centralized and distributed approaches was proposed in [5]. A three-stage resource allocation scheme which combines admission control, power allocation, and link selection was proposed in [6]. A reverse Iterative Combinatorial Auction (ICA) based resource allocation scheme was proposed in [7] for optimizing the system sum rate. The resource allocation problems in relay-aided scenarios were studied in [8], [9], and in infeasible systems where all users can not be supported simultaneously were studied in [10]. The throughput performance of the D2D underlay system with different resource sharing modes was evaluated in [11]. However, most of the previous studies mainly focus on how to maximize the Spectral Efficiency (SE) and ignore the energy consumption of UEs. Only a limited amount of works have considered the Energy Efficiency (EE) optimization problem. In practical implementation, UEs are typically handheld devices with limited battery life and can quickly run out of battery if the energy consumption is ignored in the system design. Therefore, in this paper, we focus on how to optimize the EE through resource allocation in an interference-limited environment.

For the EE optimization problem, distributed resource allocation algorithms which are based on either the reverse Iterative Combinatorial Auction (ICA) game or the bisection method were proposed in [12] and [13] respectively. However, the authors have not considered the Quality of Service (QoS) provisioning constraints and have not derived a close-form solution. Centralized resource allocation algorithms for optimizing the EE in the Device-to-MultiDevice (D2MD) or D2D-cluster scenarios were proposed in [14] and [15] respectively. One major disadvantage of the centralized algorithms is that the computational complexity and signaling overhead increase significantly with the number of UEs. Besides, since the optimization process is carried out in the BS, the optimal solution needs to be delivered to the UEs within the channel coherence time. Instead of maximizing EE, an auction-based resource allocation algorithm was proposed to maximize the battery lifetime in [16], but cellular UEs were not taken

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into consideration. A coalition game based resource sharing algorithm was proposed in [17] to jointly optimize the model selection and resource scheduling. The authors assumed that independent D2D UEs and cellular UEs can communicate with one another and act together as one entity to improve their EE in the game.

In this paper, firstly, we propose a distributed interference-aware energy-efficient resource allocation algorithm to maximize each UE's EE subject to the QoS provisioning and transmission power constraints. We model the resource allocation problem as a noncooperative game in which each player is self-interested and wants to maximize its own EE. Compared to the cooperative game model used in [17], the noncooperative model has the advantage of a lower overhead for information exchange between UEs. Both of the D2D UEs and cellular UEs are taken into consideration. The EE utility function of each player is defined as the SE divided by the total power consumption, which includes both transmission and circuit power. The formulated EE maximization problem is a non-convex problem but can be transformed into a convex optimization problem by using the nonlinear fractional programming developed in [18]. Then we prove that a Nash equilibrium exists in the noncooperative game, and the optimal resource allocation solution obtained by the proposed energy-efficient algorithm is exactly the Nash equilibrium. We also derive a spectral-efficient algorithm and compare it with the proposed energy-efficient algorithm through computer simulations. Finally, we analyze the tradeoff between EE and SE in an interference-limited environment and derive closed-form expressions of EE and SE gaps for D2D and Cellular UEs respectively.

The structure of this paper is organized as follows: Section II introduces the system model of the D2D communication underlaying cellular networks. Section III introduces the distributed iterative optimization algorithm for maximizing each UE's EE. Section IV introduces the distributed spectral-efficient resource allocation algorithm for the purpose of comparison. Section V introduces the tradeoff between EE and SE for the energy-efficient and spectral-efficient algorithms. Section VI introduces the simulation parameters, results and analyses. Section VII gives the conclusion.

## II. System Model

In this paper, we consider the uplink scenario of a single cellular network, which is composed of the base station, the D2D UEs, and the cellular UEs. Fig. 1 shows the system model of D2D communications with uplink resource sharing. There are two cellular UEs ($UE_1$ and $UE_2$), and two D2D pairs ($UE_3$ and $UE_4$, and $UE_5$ and $UE_6$ respectively). A pair of D2D transmitter and receiver form a D2D link, and a cellular UE and the BS form a cellular link. The UEs in a D2D pair are close enough to enable D2D communication. Each cellular UE is allocated with an orthogonal link (e.g., an orthogonal resource block in LTE), i.e., there is no co-channel interference between cellular UEs. At the same time, the two D2D pairs reuse the same channels allocated to cellular UEs in order to improve the spectral efficiency. As a result, the BS suffers from the interference caused by the D2D transmitters ($UE_3$ and $UE_5$), and the D2D receivers ($UE_4$ and $UE_6$) suffer from the interference caused by cellular UEs ($UE_1$ and $UE_2$) and the other D2D transmitters that reuse the same channel ($UE_5$ or $UE_3$ respectively).

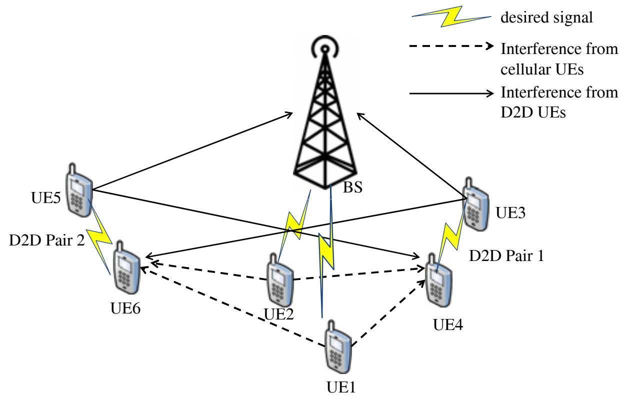


Fig. 1. System model of D2D communications with uplink channel reuse.

The set of UEs is denoted as $\mathcal{S} = \{\mathcal{N}, \mathcal{K}\}$, where $\mathcal{N}$ and $\mathcal{K}$ denote the sets of D2D UEs and cellular UEs respectively. The total number of D2D links and cellular links are denoted as $N$ and $K$ respectively. The Signal to Interference plus Noise Ratio (SINR) of the $i$-th D2D pair ($i \in \mathcal{N}$) in the $k$-th ($k \in \mathcal{K}$) channel is given by

$$\gamma_i^k = \frac{p_i^k g_i^k}{p_c^k g_{c,i}^k + \sum_{j=1, j\neq i}^{N} p_j^k g_{j,i}^k + N_0}, \tag{1}$$

where $p_i^k$, $p_c^k$, and $p_j^k$ are the transmission power of the $i$-th D2D transmitter, the $k$-th cellular UE, and the $j$-th D2D transmitter in the $k$-th channel respectively. $g_i^k$ is the channel gain of the $i$-th D2D pair, $g_{c,i}^k$ is the interference channel gain between the $k$-th cellular UE and the $i$-th D2D receiver, and $g_{j,i}^k$ is the interference channel gain between the $j$-th D2D transmitter and the $i$-th D2D receiver. $N_0$ is the nosier power. $p_c^k g_{c,i}^k$ and $\sum_{j=1, j\neq i}^{N} p_j^k g_{j,i}^k$ denote the interference from the cellular UE and the other D2D pairs that reuse the $k$-th channel respectively.

The received SINR of the $k$-th cellular UE at the BS is given by

$$\gamma_c^k = \frac{p_c^k g_c^k}{\sum_{i=1}^{N} p_i^k g_{i,c}^k + N_0}, \tag{2}$$

where $g_c^k$ is the channel gain between the $k$-th cellular UE and the BS, $g_{i,c}^k$ is the interference channel gain between the $i$-th D2D transmitter and the BS in the $k$-th channel. $\sum_{i=1}^{N} p_i^k g_{i,c}^k$ denote the interference from all of the D2D pairs to the BS in the $k$-th channel.

The achievable rates of the $i$-th D2D pair and the $k$-th cellular UE are given by

$$r_i^d = \sum_{k=1}^{K} \log_2\left(1+\gamma_i^k\right), \tag{3}$$

$$r_k^c = \log_2\left(1+\gamma_c^k\right). \tag{4}$$

The total power consumption of the $i$-th D2D pair and the $k$-th cellular UE are given by

$$p_{i,total}^d = \sum_{k=1}^{K} \frac{1}{\eta} p_i^k + 2p_{cir}, \tag{5}$$

$$p_{k,total}^c = \frac{1}{\eta} p_c^k + p_{cir}, \tag{6}$$

where $p_{i,total}^d$ is the total power consumption of the $i$-th D2D pair, which is composed of the transmission power over all of the $K$ channels, i.e., $\sum_{k=1}^{K} \frac{1}{\eta} p_i^k$, and the circuit power of both the D2D transmitter and receiver, i.e., $2p_{cir}$. The circuit power of any UE is assumed as the same and denoted as $p_{cir}$. $\eta$ is the Power Amplifier (PA) efficiency, i.e., $0 < \eta < 1$. $p_{k,total}^c$ is the total power consumption of the $k$-th cellular UE, which is composed of the transmission power $\frac{1}{\eta} p_c^k$ and the circuit power only at the transmitter side. The power consumption of the BS is not taken into consideration.

## III. Distributed Interference-Aware Energy-Efficient Resource Allocation

### A. Problem Formulation

In the centralized resource allocation, the optimization of the sum EE is carried out by the BS that requires the complete network knowledge. The computational complexity and signaling overhead increase significantly with the number of UEs. Therefore, in this section, we focus on the more practical distributed resource allocation problem, which is modeled as a noncooperative game.

In the noncooperative game, each UE is self-interested and wants to maximize its own EE. The strategy set of the $i$-th D2D transmitter is denoted as $\mathbf{p}_i^d = \{p_i^k \mid 0 \le \sum_{k=1}^{K} p_i^k \le p_{i,max}^d, k \in \mathcal{K}\}$, $\forall i \in \mathcal{N}$. The strategy set of the $k$-th cellular UE is denoted as $\mathbf{p}_k^c = \{p_c^k \mid 0 \le p_c^k \le p_{k,max}^c\}$, $\forall k \in \mathcal{K}$. $p_{i,max}^d$ and $p_{k,max}^c$ are the maximum transmission power constraints for D2D UEs and Cellular UEs respectively. The strategy set of the other D2D transmitters in $\mathcal{N}\backslash\{i\}$ is denoted as $\mathbf{p}_{-i}^d = \{p_j^k \mid 0 \le \sum_{k=1}^{K} p_j^k \le p_{j,max}^d, k \in \mathcal{K}, j \in \mathcal{N}, j \neq i\}$, $\forall i \in \mathcal{N}$. The strategy set of the other cellular UEs in $\mathcal{K}\backslash\{k\}$ is denoted as $\mathbf{p}_{-k}^c = \{p_c^m \mid 0 \le p_c^m \le p_{m,max}^c, m \in \mathcal{K}, m \neq k\}$, $\forall k \in \mathcal{K}$.

For the $i$-th D2D pair, its EE $U_{i,EE}^d$ depends not only on $\mathbf{p}_i^d$, but also on the strategies taken by other UEs in $\mathcal{S}\backslash\{i\}$, i.e., $\mathbf{p}_{-i}^d, \mathbf{p}_k^c, \mathbf{p}_{-k}^c$. $U_{i,EE}^d$ is defined as

$$\begin{aligned} &U_{i,EE}^d(\mathbf{p}_i^d, \mathbf{p}_{-i}^d, \mathbf{p}_k^c, \mathbf{p}_{-k}^c) \\ &= \frac{r_i^d}{p_{i,total}^d} = \frac{\sum_{k=1}^{K} \log_2\left(1+\frac{p_i^k g_i^k}{p_c^k g_{c,i}^k + \sum_{j=1,j\neq i}^{N} p_j^k g_{j,i}^k + N_0}\right)}{\sum_{k=1}^{K} \frac{1}{\eta} p_i^k + 2p_{cir}}. \end{aligned} \tag{7}$$

Therefore, the EE maximization problem of the $i$-th D2D pair is formulated as

$$\begin{aligned} \max. \quad & U_{i,EE}^d(\mathbf{p}_i^d, \mathbf{p}_{-i}^d, \mathbf{p}_k^c, \mathbf{p}_{-k}^c) \\ \text{s.t.} \quad & C1, C2. \end{aligned} \tag{8}$$

$$C1 : r_i^d \ge R_{i,min}^d, \tag{9}$$

$$C2 : 0 \le \sum_{k=1}^{K} p_i^k \le p_{i,max}^d. \tag{10}$$

Similarly, the EE of the $k$-th cellular UE $U_{k,EE}^c$ is defined as

$$U_{k,EE}^c(\mathbf{p}_i^d, \mathbf{p}_{-i}^d, \mathbf{p}_k^c, \mathbf{p}_{-k}^c) = \frac{r_k^c}{p_{k,total}^c} = \frac{\log_2\left(1+\frac{p_c^k g_c^k}{\sum_{i=1}^{N} p_i^k g_{i,c}^k + N_0}\right)}{\frac{1}{\eta} p_c^k + p_{cir}}. \tag{11}$$

The corresponding EE maximization problem is formulated as

$$\begin{aligned} \max. \quad & U_{k,EE}^c(\mathbf{p}_i^d, \mathbf{p}_{-i}^d, \mathbf{p}_k^c, \mathbf{p}_{-k}^c) \\ \text{s.t.} \quad & C3, C4. \end{aligned} \tag{12}$$

$$C3 : r_k^c \ge R_{k,min}^c, \tag{13}$$

$$C4 : 0 \le p_c^k \le p_{k,max}^c. \tag{14}$$

The constraints C1 and C3 specify the QoS requirements in terms of minimum transmission rate. C2 and C4 are the non-negative constraints on the power allocation variables.

### B. The Objective Function Transformation

The objective functions in (8) and (12) are non-convex due to the fractional form. In order to derive a closed-form solution, we transform the fractional objective function to a convex optimization function by using the nonlinear fractional programming developed in [18]. We define the maximum EE of the $i$-th D2D pair as $q_i^{d*}$, which is given by

$$q_i^{d*} = \max . U_{i,EE}^d(\mathbf{p}_i^d, \mathbf{p}_{-i}^d, \mathbf{p}_k^c, \mathbf{p}_{-k}^c) = \frac{r_i^d(\mathbf{p}_i^{d*})}{p_{i,total}^d(\mathbf{p}_i^{d*})}. \tag{15}$$

where $\mathbf{p}_i^{d*}$ is the best response of the $i$-th D2D transmitter given the other UEs' strategies $\mathbf{p}_{-i}^d$, $\mathbf{p}_k^c$, $\mathbf{p}_{-k}^c$. The following theorem can be proved:

***Theorem 1:*** The maximum EE $q_i^{d*}$ is achieved if and only if

$$\max. \; r_i^d(\mathbf{p}_i^d) - q_i^{d*} p_{i,total}^d(\mathbf{p}_i^d) = r_i^d(\mathbf{p}_i^{d*}) - q_i^{d*} p_{i,total}^d(\mathbf{p}_i^{d*}) = 0. \tag{16}$$

*Proof:* see Appendix A.

Similarly, for the maximum EE of the $k$-th cellular UE $q_k^{c*}$, we will have similar theorem as ***Theorem 1:***

***Theorem 2:*** The maximum EE $q_k^{c*}$ is achieved if and only if

$$\max. \; r_k^c(\mathbf{p}_k^c) - q_k^{c*} p_{k,total}^c(\mathbf{p}_k^c) = r_k^c(\mathbf{p}_k^{c*}) - q_k^{c*} p_{k,total}^c(\mathbf{p}_k^{c*}) = 0. \tag{17}$$

$\mathbf{p}_k^{c*}$ is the best response of the $k$-th cellular UE given the other UEs' strategies $\mathbf{p}_{-i}^d$, $\mathbf{p}_k^c$, $\mathbf{p}_{-k}^c$.

### C. The Iterative Optimization Algorithm

The proposed algorithm is summarized in Algorithm 1. $n$ is the iteration index, $L_{max}$ is the maximum number of iterations, and $\Delta$ is the maximum tolerance. At each iteration, for any given $q_i^d$ or $q_k^c$, the resource allocation strategy for the D2D UE or the cellular UE can be obtained by solving the following transformed optimization problems respectively:

$$\begin{aligned} &\max.\ r_i^d(\mathbf{p}_i^d) - q_i^d p_{i,total}^d(\mathbf{p}_i^d) \\ &\text{s.t. } C1, C2. \end{aligned} \tag{18}$$

$$\begin{aligned} &\max.\ r_k^c(\mathbf{p}_k^c) - q_k^c p_{k,total}^c(\mathbf{p}_k^c) \\ &\text{s.t. } C3, C4. \end{aligned} \tag{19}$$

Taking the D2D UEs as an example, the Lagrangian associated with the problem (18) is given by

$$\begin{aligned} \mathcal{L}_{EE}(\mathbf{p}_i^d, \alpha_i, \beta_i) &= r_i^d(\mathbf{p}_i^d) - q_i^d p_{i,total}^d(\mathbf{p}_i^d) \\ &- \alpha_i \left( r_i^d - R_{i,min}^d \right) - \beta_i \left( \sum_{k=1}^{K} p_i^k - p_{i,max}^d \right), \end{aligned} \tag{20}$$

where $\alpha_i$, $\beta_i$ are the Lagrange multipliers associated with the constraints C1 and C2 respectively. The constraint $p_i^k \geq 0$ is absorbed into the Karush-Kuhn-Tucker (KKT) condition when solving the equivalent Lagrange dual problem:

$$\min_{(\alpha_i \geq 0, \beta_i \geq 0)} . \ \max_{(\mathbf{p}_i^d)} . \ \mathcal{L}_{EE}(\mathbf{p}_i^d, \alpha_i, \beta_i) \tag{21}$$

It is noted that the objective function in (18) is a concave function of $p_i^k$ ($p_i^k \in \mathbf{p}_i^d$), and the primal and dual optimal points form an saddle-point of the Lagrangian. The dual problem in (21) can be decomposed into two subproblems: the maximization problem solves the power allocation problem to find the best strategy and the minimization problem solves the master dual problem to find the corresponding Lagrange multipliers. For any given $q_i^d$, the solution is given by

$$p_i^k = \left[ \frac{\eta(1-\alpha_i)\log_2 e}{q_i^d + \eta\beta_i} - \frac{p_c^k g_{c,i}^k + \sum_{j=1, j\neq i}^{N} p_j^k g_{j,i}^k + N_0}{g_i^k} \right]^+, \tag{22}$$

where $[x]^+ = \max\{0, x\}$. Equation (22) indicates a water-filling algorithm for transmission power allocation, and the interference from the other UEs decreases the water level. For solving the minimization problem, the Lagrange multipliers can be updated by using the subgradient method [19], [20] as

$$\alpha_i(\tau+1) = \left[ \alpha_i(\tau) - \mu_{i,\alpha}(\tau) \left( r_i^d(\tau) - R_{i,min}^d \right) \right]^+, \tag{23}$$

$$\beta_i(\tau+1) = \left[ \beta_i(\tau) - \mu_{i,\beta}(\tau) \left( \sum_{k=1}^{K} p_i^k(\tau) - p_{i,max}^d \right) \right]^+, \tag{24}$$

where $\tau$ is the iteration index, $\mu_{i,\alpha}, \mu_{i,\beta}$ are the positive step sizes. The solution of problem (21) converges to the optimum solution in (18) if the step sizes are chosen to satisfy the diminishing step size rules [20]. Since the Lagrange multiplier updating techniques are beyond the scope of this paper, interested readers may refer to [19], [20] and references therein for details.

**Algorithm 1** Iterative Resource Allocation Algorithm

$q_i^d \leftarrow 0$, $q_k^c \leftarrow 0$, $L_{max} \leftarrow 10$, $n \leftarrow 1$, $\Delta \leftarrow 10^{-3}$
**for** $n = 1$ to $L_{max}$ **do**
  **if** D2D link **then**
    solve (18) for a given $q_i^d$ and obtain the set of strategies $\mathbf{p}_i^d$
    **if** $r_i^d(\mathbf{p}_i^d) - q_i^d p_{i,total}^d(\mathbf{p}_i^d) \leq \Delta$, **then**
      $\mathbf{p}_i^{d*} = \mathbf{p}_i^d$, and $q_i^{d*} = \dfrac{r_i^d(\mathbf{p}_i^{d*})}{p_{i,total}^d(\mathbf{p}_i^{d*})}$
      **break**
    **else**
      $q_i^d = \dfrac{r_i^d(\mathbf{p}_i^d)}{p_{i,total}^d(\mathbf{p}_i^d)}$, and $n = n + 1$
    **end if**
  **else**
    solve (19) for a given $q_k^c$ and obtain the set of strategies $\mathbf{p}_k^c$
    **if** $r_k^c(\mathbf{p}_k^c) - q_k^c p_{k,total}^c(\mathbf{p}_k^c) \leq \Delta$, **then**
      $\mathbf{p}_k^{c*} = \mathbf{p}_c$, and $q_k^{c*} = \dfrac{r_k^c(\mathbf{p}_k^{c*})}{p_{k,total}^c(\mathbf{p}_k^{c*})}$
      **break**
    **else**
      $q_k^c = \dfrac{r_k^c(\mathbf{p}_k^c)}{p_{k,total}^c(\mathbf{p}_k^c)}$, and $n = n + 1$
    **end if**
  **end if**
**end for**

Similarly, the optimum solution of $p^c$ is given by

$$p_c^k = \left[ \frac{\eta(1-\delta_k)\log_2 e}{q_k^c + \eta\theta_k} - \frac{\sum_{i=1}^{N} p_i^k g_{i,c}^k + N_0}{g_c^k} \right]^+, \tag{25}$$

where $\delta_k, \theta_k$ are the Lagrange multipliers associated with the constraints C3 and C4 respectively.

A Nash equilibrium is a set of power allocation strategies that none UE (neither D2D UE nor cellular UE) can unilaterally improve its EE by choosing a different power allocation strategy, i.e., $\forall i \in \mathcal{N}, \forall k \in \mathcal{K}$,

$$U_{i,EE}^d(\mathbf{p}_i^{d*}, \mathbf{p}_{-i}^{d*}, \mathbf{p}_k^{c*}, \mathbf{p}_{-k}^{c*}) \geq U_{i,EE}^d(\mathbf{p}_i^d, \mathbf{p}_{-i}^d, \mathbf{p}_k^c, \mathbf{p}_{-k}^c), \tag{26}$$

$$U_{k,EE}^c(\mathbf{p}_i^{d*}, \mathbf{p}_{-i}^{d*}, \mathbf{p}_k^{c*}, \mathbf{p}_{-k}^{c*}) \geq U_{k,EE}^c(\mathbf{p}_i^d, \mathbf{p}_{-i}^d, \mathbf{p}_k^c, \mathbf{p}_{-k}^c). \tag{27}$$

***Theorem 3:*** A Nash equilibrium exists in the noncooperaive game. Furthermore, the strategy set $\{\mathbf{p}_i^{d*}, \mathbf{p}_k^{c*} \mid i \in \mathcal{N}, k \in \mathcal{K}\}$ obtained by using Algorithm 1 is the Nash equilibrium.

*Proof:* see Appendix B.

## IV. Distributed Interference-Aware Spectral-Efficient Resource Allocation

In this section, for the purpose of comparison, we derive the distributed interference-aware spectral-efficient resource allocation by employing the noncooperative game model developed in Section III. Each UE is self-interested and wants to maximize its own SE rather than EE, and the power consumption is completely ignored in the optimization process. For the $i$-th D2D pair, its SE utility function $U^d_{i,SE}$ depends not only on $\mathbf{p}^d_i$, but also on the strategies taken by other UEs in $\mathcal{S}\backslash\{i\}$, i.e., $\mathbf{p}^d_{-i}$, $\mathbf{p}^c_k$, $\mathbf{p}^c_{-k}$. $U^d_{i,SE}$ is defined as

$$\begin{aligned} &U^d_{i,SE}(\mathbf{p}^d_i, \mathbf{p}^d_{-i}, \mathbf{p}^c_k, \mathbf{p}^c_{-k}) \\ &= r^d_i = \sum_{k=1}^{K} \log_2\left(1 + \frac{p^k_i g^k_i}{p^k_c g^k_{c,i} + \sum_{j=1,j\neq i}^{N} p^k_j g^k_{j,i} + N_0}\right). \end{aligned} \tag{28}$$

Therefore, the SE maximization problem of the $i$-th D2D pair is formulated as

$$\begin{aligned} \max.\quad & U^d_{i,SE}(\mathbf{p}^d_i, \mathbf{p}^d_{-i}, \mathbf{p}^c_k, \mathbf{p}^c_{-k}) \\ \text{s.t.}\quad & C1, C2. \end{aligned} \tag{29}$$

Similarly, the SE of the $k$-th cellular UE $U^c_{k,SE}$ is defined as

$$U^c_{k,SE}(\mathbf{p}^d_i, \mathbf{p}^d_{-i}, \mathbf{p}^c_k, \mathbf{p}^c_{-k}) = r^c_k = \log_2\left(1 + \frac{p^k_c g^k_c}{\sum_{i=1}^{N} p^k_i g^k_{i,c} + N_0}\right). \tag{30}$$

The corresponding SE maximization problem is formulated as

$$\begin{aligned} \max.\quad & U^c_{k,SE}(\mathbf{p}^d_i, \mathbf{p}^d_{-i}, \mathbf{p}^c_k, \mathbf{p}^c_{-k}) \\ \text{s.t.}\quad & C3, C4. \end{aligned} \tag{31}$$

It is noted that the objective functions in (29) and (31) are concave and closed-form solution can be derived by exploiting the properties of convex optimization. Taking the D2D UEs as an example, given the other UEs' strategies $\mathbf{p}^d_{-i}$, $\mathbf{p}^c_k$, $\mathbf{p}^c_{-k}$, the Lagrangian associated with the problem (29) is given by

$$\begin{aligned} &\mathcal{L}_{SE}(\mathbf{p}^d_i, \alpha_i, \beta_i) \\ &= r^d_i(\mathbf{p}^d_i) - \alpha_i\left(r^d_i(\mathbf{p}^d_i) - R^d_{i,min}\right) - \beta_i\left(\sum_{k=1}^{K} p^k_i - p^d_{i,max}\right), \end{aligned} \tag{32}$$

where $\alpha_i$, $\beta_i$ are the Lagrange multipliers associated with the constraints C1 and C2 respectively. The equivalent Lagrange dual problem:

$$\min_{(\alpha_i \geq 0, \beta_i \geq 0)} \; \max_{(\mathbf{p}^d_i)} \; \mathcal{L}_{SE}(\mathbf{p}^d_i, \alpha_i, \beta_i). \tag{33}$$

The dual problem in (33) can be decomposed into two subproblems: the maximization problem solves the power allocation problem to find the best strategy and the minimization problem solves the master dual problem to find the corresponding Lagrange multipliers. For any given $\alpha_i$,$\beta_i$, the solution is given by

$$p^{k*}_i = \left[\frac{(1-\alpha_i)\log 2e}{\beta_i} - \frac{p^{k*}_c g^k_{c,i} + \sum_{j=1,j\neq i}^{N} p^k_j g^k_{j,i} + N_0}{g^k_i}\right]^+. \tag{34}$$

Equation (34) indicates a water-filling algorithm for transmission power allocation, and the interference from the other UEs decreases the water level. The Lagrange multipliers can be updated by using the subgradient method [19], [20], which is introduced in Section III.

Similarly, the optimum solution of $p^{k*}_c$ is given by

$$p^{k*}_c = \left[\frac{(1-\delta_k)\log_2 e}{\theta_k} - \frac{\sum_{i=1}^{N} p^{k*}_i g^k_{i,c} + N_0}{g^k_c}\right]^+, \tag{35}$$

where $\delta_k, \theta_k$ are the Lagrange multipliers associated with the constraints C3 and C4 respectively.

A Nash equilibrium is a set of power allocation strategies that none UE (neither D2D UE nor cellular UE) can unilaterally improve its SE by choosing a different power allocation strategy, i.e., $\forall i \in \mathcal{N}, \forall k \in \mathcal{K}$,

$$U^d_{i,SE}(\mathbf{p}^{d*}_i, \mathbf{p}^{d*}_{-i}, \mathbf{p}^{c*}_k, \mathbf{p}^{c*}_{-k}) \geq U^d_{i,SE}(\mathbf{p}^d_i, \mathbf{p}^d_{-i}, \mathbf{p}^c_k, \mathbf{p}^c_{-k}), \tag{36}$$

$$U^c_{k,SE}(\mathbf{p}^{d*}_i, \mathbf{p}^{d*}_{-i}, \mathbf{p}^{c*}_k, \mathbf{p}^{c*}_{-k}) \geq U^c_{k,SE}(\mathbf{p}^d_i, \mathbf{p}^d_{-i}, \mathbf{p}^c_k, \mathbf{p}^c_{-k}). \tag{37}$$

***Theorem 4:*** A Nash equilibrium exists in the noncooperaive game. Furthermore, the strategy set $\{\mathbf{p}^{d*}_i, \mathbf{p}^{c*}_k \mid i \in \mathcal{N}, k \in \mathcal{K}\}$ obtained by (34), (35) is the Nash equilibrium.

*Proof:* see Appendix C

## V. Energy Efficiency and Spectral Efficiency Tradeoff

In this section, we investigate the tradeoff between EE and SE. For the $i$-th D2D pair, the EE gap between the energy-efficient algorithm and the spectral-efficient algorithm, which are derived in Section III and Section IV respectively, is defined as

$$\begin{aligned} G^d_{i,EE} &= U^{d*}_{i,EE} - \frac{U^{d*}_{i,SE}}{(p^d_{i,total})_{SE}} \\ &= \frac{\sum_{k=1}^{K} \log_2\left(1 + \frac{p^{k*}_{i,EE} g^k_i}{p^{k*}_{c,EE} g^k_{c,i} + \sum_{j=1,j\neq i}^{N} p^{k*}_{j,EE} g^k_{j,i} + N_0}\right)}{\sum_{k=1}^{K} \frac{1}{\eta} p^{k*}_{i,EE} + 2p_{cir}} \\ &\quad - \frac{\sum_{k=1}^{K} \log_2\left(1 + \frac{p^{k*}_{i,SE} g^k_i}{p^{k*}_{c,SE} g^k_{c,i} + \sum_{j=1,j\neq i}^{N} p^{k*}_{j,SE} g^k_{j,i} + N_0}\right)}{\sum_{k=1}^{K} \frac{1}{\eta} p^{k*}_{i,SE} + 2p_{cir}}, \end{aligned} \tag{38}$$

where $U^{d*}_{i,EE}$ and $U^{d*}_{i,SE}$ are the maximum EE and SE which are obtained by solving the problems in (8) and (29) respectively. $p^{k*}_{i,EE}$ and $p^{k*}_{c,EE}$ are the optimal energy-efficient power allocation solution given by Algorithm 1 (using (22) and (25) respectively). $p^{k*}_{i,SE}$ and $p^{k*}_{c,SE}$ are the optimal spectral-efficient power allocation solution given by (34) and (35) respectively. The SE gap between the spectral-efficient algorithm and the energy-efficient algorithm is defined as

$$\begin{aligned} G^d_{i,SE} &= U^{d*}_{i,SE} - (p^d_{i,total})_{EE} U^{d*}_{i,EE} \\ &= \sum_{k=1}^{K} \log_2\left(1 + \frac{p^{k*}_{i,SE} g^k_i}{p^{k*}_{c,SE} g^k_{c,i} + \sum_{j=1,j\neq i}^{N} p^{k*}_{j,SE} g^k_{j,i} + N_0}\right) \\ &\quad - \sum_{k=1}^{K} \log_2\left(1 + \frac{p^{k*}_{i,EE} g^k_i}{p^{k*}_{c,EE} g^k_{c,i} + \sum_{j=1,j\neq i}^{N} p^{k*}_{j,EE} g^k_{j,i} + N_0}\right). \end{aligned} \tag{39}$$

Similarly, for the $k$-th cellular UE, the EE and SE gaps between the energy-efficient and the spectral-efficient algorithms are given by

$$G^c_{k,EE} = U^{c*}_{k,EE} - \frac{U^{c*}_{k,EE}}{(p^c_{k,total})_{SE}} = \frac{\log_2\left(1 + \frac{p^{k*}_{c,EE}g^k_c}{\sum_{i=1}^N p^{k*}_{i,EE}g^k_{i,c}+N_0}\right)}{\frac{1}{\eta}p^{k*}_{c,EE} + p_{cir}} - \frac{\log_2\left(1 + \frac{p^{k*}_{c,SE}g^k_c}{\sum_{i=1}^N p^{k*}_{i,SE}g^k_{i,c}+N_0}\right)}{\frac{1}{\eta}p^{k*}_{c,SE} + p_{cir}}, \quad (40)$$

$$G^c_{k,SE} = U^{c*}_{k,SE} - (p^c_{k,total})_{EE}U^{c*}_{k,EE} = \log_2\left(1 + \frac{p^{k*}_{c,SE}g^k_c}{\sum_{i=1}^N p^{k*}_{i,SE}g^k_{i,c} + N_0}\right) - \log_2\left(1 + \frac{p^{k*}_{c,EE}g^k_c}{\sum_{i=1}^N p^{k*}_{i,EE}g^k_{i,c} + N_0}\right), \quad (41)$$

where $U^{c*}_{k,EE}$ and $U^{c*}_{k,SE}$ are the maximum EE and SE which are obtained by solving (12) and (31) respectively.

Although the EE and SE gaps can be calculated by using (38), (39), (40), (41), the numerical results depends on the specific channel realization in each simulation and a large number of simulations are required to obtain the average result. In order to facilitate analysis and get some insights, we consider a special case that all the signal channels have the same power gain $g$, and all the interference channels have the same power gain $\hat{g}$. The interference level of the overall network is defined as $I = \frac{\hat{g}}{g}$. The EE and SE gaps defined in (38), (39), (40), (41) can be rewritten as

$$G^d_{i,EE} = \frac{K\log_2\left(1 + \frac{p^{k*}_{i,EE}}{p^{k*}_{c,EE}I+(N-1)p^{k*}_{i,EE}I+\frac{N_0}{g}}\right)}{\frac{K}{\eta}p^{k*}_{i,EE} + 2p_{cir}} - \frac{K\log_2\left(1 + \frac{p^{k*}_{i,SE}}{p^{k*}_{c,SE}I+Np^{k*}_{j,SE}I+\frac{N_0}{g}}\right)}{\frac{K}{\eta}p^{k*}_{i,SE} + 2p_{cir}}, \quad (42)$$

$$G^d_{i,SE} = K\log_2\left(1 + \frac{p^{k*}_{i,SE}}{p^{k*}_{c,SE}I + (N-1)p^{k*}_{i,SE}I + \frac{N_0}{g}}\right) - K\log_2\left(1 + \frac{p^{k*}_{i,EE}}{p^{k*}_{c,EE}I + Np^{k*}_{i,EE}I + \frac{N_0}{g}}\right), \quad (43)$$

$$G^c_{k,EE} = \frac{\log_2\left(1 + \frac{p^{k*}_{c,EE}}{Np^{k*}_{i,EE}I+\frac{N_0}{g}}\right)}{\frac{1}{\eta}p^{k*}_{c,EE} + p_{cir}} - \frac{\log_2\left(1 + \frac{p^{k*}_{c,SE}}{Np^{k*}_{i,SE}I+\frac{N_0}{g}}\right)}{\frac{1}{\eta}p^{k*}_{c,SE} + p_{cir}}, \quad (44)$$

$$G^c_{k,SE} = \log_2\left(1 + \frac{p^{k*}_{c,SE}}{Np^{k*}_{i,SE}I + \frac{N_0}{g}}\right) - \log_2\left(1 + \frac{p^{k*}_{c,EE}}{Np^{k*}_{i,EE}I + \frac{N_0}{g}}\right). \quad (45)$$

TABLE I. SIMULATION PARAMETERS.

| Parameter | Value |
|---|---|
| Cell radius | 500 m |
| Maximum D2D transmission distance | 25 m |
| Maximum transmission power $p^d_{i,max}, p^c_{k,max}$ | 200 mW (23 dBm) |
| Constant circuit power $p_{cir}$ | 10 mW (10 dBm) |
| Thermal noise power $N_0$ | $10^{-7}$ W |
| Number of D2D pairs $N$ | 5 |
| Number of cellular UEs $K$ | 3 |
| PA efficiency $\eta$ | 35% |
| QoS of cellular UEs $R^c_{k,min}$ | 0.1 bit/s/Hz |
| QoS of D2D UEs $R^d_{i,min}$ | 0.5 bit/s/Hz |

The relationships among the EE and SE tradeoff, the EE and SE gap, and the inreference level are analyzed through simulations by using the equations derived above.

## VI. SIMULATION RESULTS

In this section, the proposed algorithm is verified through computer simulations. The values of simulation parameters are inspired by [4], [7], [12] , and are summarized in Table I. We compare the proposed EE maximization algorithm (labeled as "energy-efficient") with the SE maximization algorithm (labeled as "spectral-efficient" ), and the random power allocation algorithm (labeled as "random"). The results are averaged through a total number of 1000 simulations and normalized by the maximum value. For each simulation, the locations of the cellular UEs and D2D UEs are generated randomly within a cell with a radius of 500 m. Fig. 2 shows the locations of D2D UEs and cellular UEs generated in one simulation. The maximum distance between any two D2D UEs that form a D2D pair is 25 m. The channel gain between the transmitter $i$ and the receiver $j$ is calculated as $d^{-2}_{i,j}|h_{i,j}|^2$ [4], [12], [16], where $d_{i,j}$ is the distance between the transmitter $i$ and the receiver $j$, $h_{i,j}$ is the complex Gaussian channel coefficient that satisfies $h_{i,j} \sim \mathcal{CN}(0, 1)$.

Fig. 3 shows the normalized average EE of D2D links corresponding to the number of game iterations. The normalized average EE of the proposed energy-efficient algorithm converge to 0.429, while the random algorithm converge to 0.124 and the spectral-efficient algorithm converge to 0.064. It is clear that the proposed energy-efficient algorithm significantly outperforms the spectral-efficient algorithm and the random algorithm in terms of EE in an interference-limited environment. The spectral-efficient algorithm has the worst EE performance among the three because power consumption is completely ignored in the optimization process.

Fig. 4 shows the normalized average EE of cellular links corresponding to the number of game iterations. The simulation results demonstrate that the proposed algorithm achieves the best performance again. Comparing Fig. 4 with Fig. 3, we find that the D2D links can achieve a much better EE than the cellular links due to the proximity gain and the channel reuse gain. The proposed energy-efficient algorithm and the conventional SE algorithm converges to the equilibrium within $3 \sim 4$ game iterations, while the random algorithm fluctuates around the equilibrium since that the transmission power strategy is randomly selected.

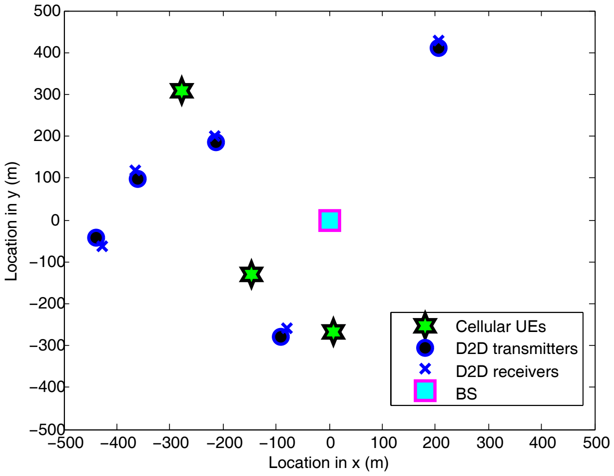


Fig. 2. The locations of D2D UEs and cellular UEs generated in one simulation ($N$ = 5, $K$ = 3, the cell radius is 500 m, and maximum D2D distance is 25 m ). A total of 1000 simulations are performed.

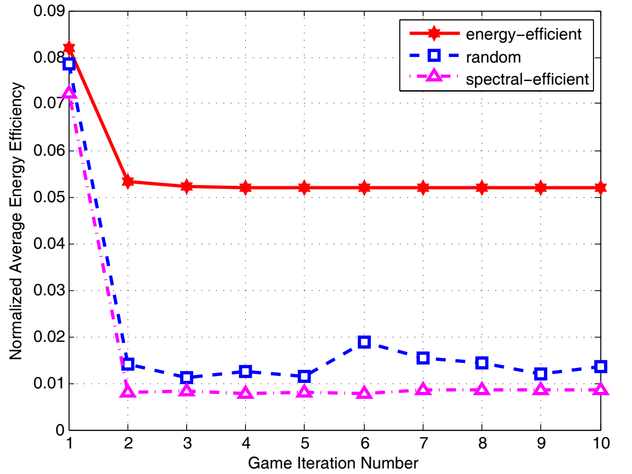


Fig. 4. The normalized average energy efficiency of cellular links corresponding to the number of game iterations ($N = 5$, $K = 3$, $p^d_{i,max} = p^c_{k,max} = 200$ mW, $R^c_{k,min} = 0.1$ bit/s/Hz, $R^d_{i,min} = 1$ bit/s/Hz, 1000 simulations).

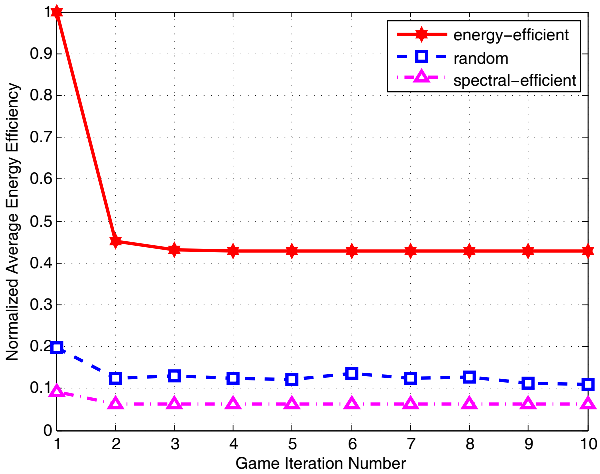


Fig. 3. The normalized average energy efficiency of D2D links corresponding to the number of game iterations ($N = 5$, $K = 3$, $p^d_{i,max} = p^c_{k,max} = 200$ mW, $R^c_{k,min} = 0.1$ bit/s/Hz, $R^d_{i,min} = 1$ bit/s/Hz, 1000 simulations).

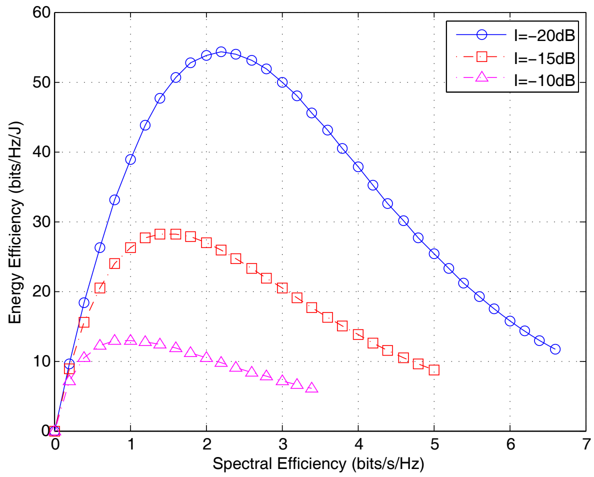


Fig. 5. The energy efficiency and spectral efficiency tradeoff for cellular UEs corresponding to three interference levels $I = -20, -15, -10$ dB, ($g = 1, N = 1, K = 1$, $p^d_{i,max} = p^c_{k,max} = 200$ mW).

Fig. 5 shows the tradeoff between EE and SE for the cellular UE under different interference scenarios, i.e., $I = -15, -10, -5$ dB. We consider the special case discussed in Section V. The SE of the cellular UE is increased from 0 bits/s/Hz to 7 bits/s/Hz with a step of 0.2, and the corresponding transmission power $p^k_c$ is calculated by using (2) and (4). We assume that the D2D transmitter is selfish and always use the maximum transmission power. For each step of SE, the corresponding EE is obtained through simulations.

For the case of $I = -15$ dB, the maximum achievable SE and EE subject to the transmission power constraint are 6.6 bits/s/Hz and 54.26 bits/s/J respectively. In comparison, for the case of $I = -10$ dB, the maximum achievable SE and EE are 5 bits/s/Hz and 28.21 bits/s/J respectively. By increasing the interference level from $-15$ dB to $-10$ dB, the maximum achievable SE and EE are reduced by nearly 24% and 48% respectively. We conclude that as interference level increases, the EE decreases more rapidly than the SE. Furthermore, if we further increase the transmission power, the EE degrades severely while the SE only improves slightly. For example, when $I = -15$ dB, if we increase the SE from 2.2 bits/s/Hz to 4 bits/s/Hz, the corresponding EE is reduced from 54.26 bits/s/J to 37.83 bits/s/J. As a result, the SE is only increased by 1.8 bits/s/Hz, but the EE is reduced by 16.43 bits/Hz/J.

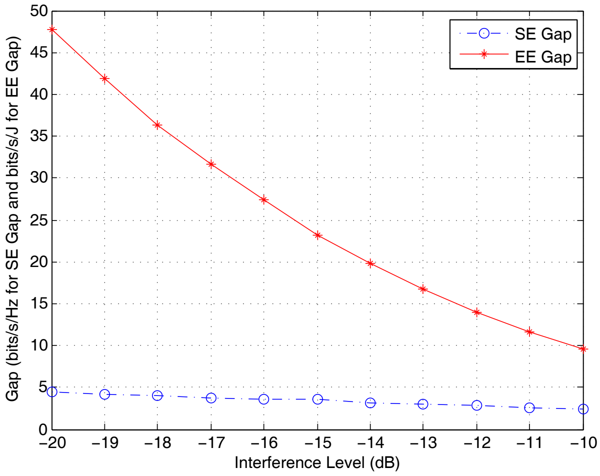


Fig. 6. The energy efficiency and spectral efficiency gaps of the cellular UE with regards to the interference level $I$ ($g = 1, N = 1, K = 1$, $p^d_{i,max} = p^c_{k,max} =$ 200 mW).

Hence, increasing transmission power beyond the power for optimal EE brings little SE improvement but significant EE loss. However, in the severe interference case, i.e., $I = -5$dB, the EE loss is not so large due to the fact that the maximum achievable EE is limited by the interference.

Fig. 6 shows the EE and SE gaps of the cellular UE (defined in (44) and (45) respectively) with regards to the interference level $I$. From Fig. 6, it is clear that both the EE and SE gaps ($G^c_{i,EE}$ and $G^c_{i,SE}$) decrease as the interference level $I$ increasing. In particular, the EE gap decreases much more rapidly than the SE gap, which verifies again that in an interference-limited environment, increasing transmission power beyond the power for optimal EE brings little SE improvement but significant EE loss. Therefore, the proposed energy-efficient algorithm can bring significant EE improvement subject to little SE loss.

## VII. Conclusion

In this paper, we proposed a distributed interference-aware energy-efficient resource allocation algorithm for D2D communications by exploiting the properties of the nonlinear fractional programming. Simulation results have demonstrated that the proposed energy-efficient algorithm significantly outperforms the spectral-efficient algorithm in terms of EE for both cellular and D2D links. We have analyzed the tradeoff between EE and SE and derived closed-form expressions for EE and SE gaps. Through simulation results we found that in an interference-limited environment, increasing transmission power beyond the power for optimal EE brings little SE improvement but significant EE loss. Therefore, the proposed energy-efficient algorithm can bring significant EE improvement subject to little SE loss.

## Appendix A
## Proof of the Theorem 1

The proof of the Theorem 1 is similar to the proof of the Theorem (page 494 in [18]). Firstly, we prove the necessity proof. For any feasible strategy set $\mathbf{p}^d_i$, $\forall i \in \mathcal{N}$, we have

$$q^{d*}_i = \frac{r^d_i(\mathbf{p}^{d*}_i)}{p^d_{i,total}(\mathbf{p}^{d*}_i)} \geq \frac{r^d_i(\mathbf{p}^d_i)}{p^d_{i,total}(\mathbf{p}^d_i)}. \tag{46}$$

By rearranging (46), we obtain

$$r^d_i(\mathbf{p}^{d*}_i) - q^{d*}_i p^d_{i,total}(\mathbf{p}^{d*}_i) = 0, \tag{47}$$

$$r^d_i(\mathbf{p}^d_i) - q^{d*}_i p^d_{i,total}(\mathbf{p}^d_i) \leq 0. \tag{48}$$

Hence, the maximum value of $r^d_i(\mathbf{p}^d_i) - q^{d*}_i p^d_{i,total}(\mathbf{p}^d_i)$ is 0, and can only be achieved by $\mathbf{p}^{d*}_i$, which is obtained by solving the EE maximization problem defined in (8). This completes the necessity proof.

Now we turn to the sufficiency proof. Assume that $\tilde{\mathbf{p}}^d_i$ is the optimal solution which satisfies that

$$r^d_i(\mathbf{p}^d_i) - q^{d*}_i p^d_{i,total}(\mathbf{p}^d_i) \leq r^d_i(\tilde{\mathbf{p}}^d_i) - q^{d*}_i p^d_{i,total}(\tilde{\mathbf{p}}^d_i) = 0. \tag{49}$$

By rearranging (49), we have

$$q^{d*}_i = \frac{r^d_i(\tilde{\mathbf{p}}^d_i)}{p^d_{i,total}(\tilde{\mathbf{p}}^d_i)} \geq \frac{r^d_i(\mathbf{p}^d_i)}{p^d_{i,total}(\mathbf{p}^d_i)}. \tag{50}$$

Hence, $\tilde{\mathbf{p}}^d_i$ is also the solution of the EE maximization problem defined in (8), i.e., $\tilde{\mathbf{p}}^d_i = \mathbf{p}^{d*}_i$. This completes the sufficiency proof.

## Appendix B
## Proof of the Theorem 3

According to [21], a Nash equilibrium exists if the utility function is continuous and quasiconcave, and the set of strategies is a nonempty compact convex subset of a Euclidean space. Taking the EE objection function defined in (7) as an example, the numerator $r^d_i$ defined in (3) is a concave function of $p^k_i$, $\forall i \in \mathcal{N}, k \in \mathcal{K}$. The denominator defined in (5) is an affine function of $p^k_i$. Therefore, $U^d_{i,EE}$ is quasiconcave (Problem 4.7 in [22]). The set of the strategies $\mathbf{p}^d_i = \{p^k_i \mid 0 \leq \sum_{k=1}^K p^k_i \leq p^d_{i,max}, k \in \mathcal{K}\}$, $\forall i \in \mathcal{N}$, is a nonempty compact convex subset of the Euclidean space $\mathbb{R}^K$. Similarly, it is easily proved that the above conditions also hold for the cellular UE. Therefore, a Nash equilibrium exists in the noncooperaive game.

If the strategy set $\mathbf{p}^{d*}_i$ obtained by using Algorithm 1 is not the Nash equilibrium, the $i$-th D2D transmitter can choose the Nash equilibrium $\hat{\mathbf{p}}^d_i$ ($\hat{\mathbf{p}}^d_i \neq \mathbf{p}^{d*}_i$) to obtain the maximum EE $q^{d*}_i$. However, by Theorem 1, $q^{d*}_i$ can only be achieved by choosing $\mathbf{p}^{d*}_i$. Then, we must have $\hat{\mathbf{p}}^d_i = \mathbf{p}^{d*}_i$, which contradicts with the assumption. Therefore, $\mathbf{p}^{d*}_i$ is part of the Nash equilibrium. A similar proof holds for $\mathbf{p}^{c*}_k$. It is proved that the set $\{\mathbf{p}^{d*}_i, \mathbf{p}^{c*}_k \mid i \in \mathcal{N}, k \in \mathcal{K}\}$ obtained by using Algorithm 1 is the Nash equilibrium.

## Appendix C
## Proof of the Theorem 4

According to [21], a Nash equilibrium exists if the utility function is continuous and quasiconcave, and the set of strategies is a nonempty compact convex subset of a Euclidean space. Taking the SE objection function defined in (28) as an example, $r_i^d$ defined in (3) is a concave function of $p_i^k$, $\forall i \in \mathcal{N}, k \in \mathcal{K}$. Therefore, $U_{i,EE}^d$ is quasiconcave since any concave function is quasiconcave [22]. The set of the strategies $\mathbf{p}_i^d = \{p_i^k \mid 0 \le \sum_{k=1}^K p_i^k \le p_{i,max}^d, k \in \mathcal{K}\}$, $\forall i \in \mathcal{N}$, is a nonempty compact convex subset of the Euclidean space $\mathbb{R}^K$. Similarly, it is easily proved that the above conditions also hold for the cellular UE. Therefore, a Nash equilibrium exists in the noncooperaive game.

If the strategy set $\mathbf{p}_i^{d*}$ obtained by (34) is not the Nash equilibrium, the $i$-th D2D transmitter can choose the Nash equilibrium $\hat{\mathbf{p}}_i^d$ ($\hat{\mathbf{p}}_i^d \neq \mathbf{p}_i^{d*}$) to obtain the maximum SE defined in (29). Hence, $\hat{\mathbf{p}}_i^d$ is also the solution of the SE maximization problem defined in (29), i.e., $\hat{\mathbf{p}}_i^d = \mathbf{p}_i^{d*}$. This completes the proof.

## Acknowledgment

This work was partially supported by National Science Foundation of China (NSFC) under Grant Number 61203100 and Fundamental Research Funds for the Central Universities under Grant Number 13MS19, 14MS11, China Mobile Communication Co. Ltd. Research Institute (CMRI), and China Electric Power Research Institute (CEPRI) of State Grid Corporation of China (SGCC).

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